ANL/ESD/12-5 Rev. 5

Carbon Calculator for Land Use Change from Biofuels Production (CCLUB)

Users' Manual and Technical Documentation

Energy Systems Division

ANL/ESD/12-5 Rev. 5

Carbon **C**alculator for **L**and **U**se Change from **B**iofuels Production (CCLUB)

Users' Manual and Technical Documentation

by
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Version Notes

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1. Introduction

The Carbon Calculator for Land Use Change from Biofuels Production (CCLUB) model calculates greenhouse gas (GHG) emissions from land use change (LUC) for four different ethanol production pathways including corn grain ethanol and cellulosic ethanol from corn stover, *Miscanthus*, and switchgrass, and a soy biodiesel pathway. This document discusses the version of CCLUB released September 30, 2018, which includes five ethanol LUC scenarios and four soy biodiesel LUC scenarios.

Figure 1 outlines the calculations and data sources within CCLUB that are described in this document. Table 1 identifies where these data are stored and used within the CCLUB model, which is built in MS Excel. Purdue University's Global Trade Analysis Project (GTAP) model, a computable general equilibrium (CGE) economic model, has been used to estimate changes in land use in response to increased biofuel production. Section 0 describes the GTAP data CCLUB uses and how these data were modified to reflect shrubland transitions. Feedstock- and spatially-explicit belowground carbon content data for the United States were generated with a surrogate model for CENTURY's soil organic carbon sub-model (SCSOC) (Kwon and Hudson 2010) as described in Section 3. CENTURY is a soil organic matter model developed by Parton *et al.* (1987). The version of CCLUB released in 2012 used SCSOC-derived carbon content data at the state level. Starting with the version released in 2013, CCLUB used soil carbon data at the county level for the United States. Aboveground non-soil carbon content data for forest ecosystems was sourced from the Carbon Online Estimator (COLE) (Van Deusen and Heath 2013). COLE is based on the U.S. Forest Service Inventory and Analysis and Resource Planning Assessment data, in addition to other ecological data, as explained in Section 4. COLE data are included in CCLUB at the county level. We discuss emission factors used for calculation of international GHG emissions in Section 5. Land management change (LMC) was incorporated into CCLUB in the 2015 release. Land management change scenarios include the adoption of cover crops and the application of manure on corn fields from which either 0 or 30% of stover is removed as a biofuel feedstock. An independent report has been released in 2015 to document the data, methodology and assumptions behind this practice (Section 6). Starting in 2016, additional estimates were included in CCLUB to assess domestic and international nitrous oxide (N_2O) emissions associated with LUC. In 2017, CCLUB was expanded to estimate LUC emissions for soy biodiesel, incorporating four LUC cases and associated soil organic carbon (SOC) change updates related to soy biodiesel pathways. LUC was estimated by GTAP, and SOC change was based on SCSOC.

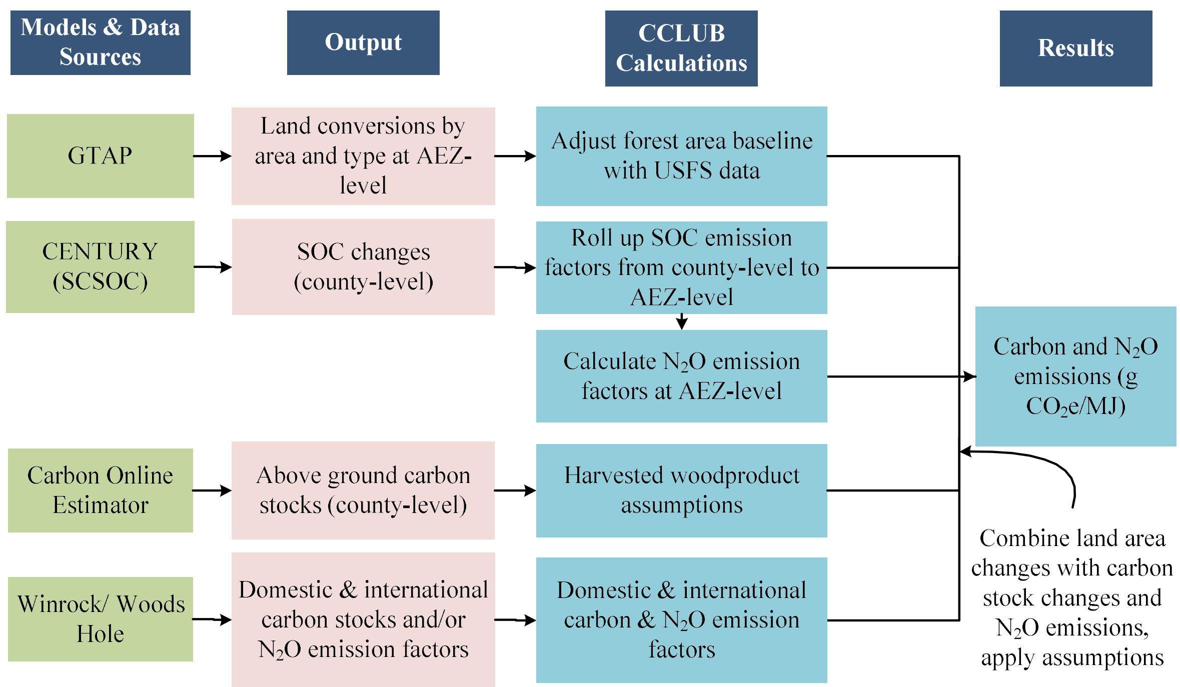

Figure 1. Schematic of Data Sources and Calculations in CCLUB. As explained in Section 5, Woods Hole data can be used as an alternative dataset to Winrock for international carbon stocks. Woods Hole data and Winrock data can be used for domestic carbon stocks. Winrock data also include international methane (CH_4) and N_2O emissions.

Table 1. Overview of CCLUB Worksheets

Worksheet	Description
Overview	Information on CCLUB related documentation
Scenario & Results	Displays results and enables selection of data sources, key assumptions, and biofuels scenarios. Two worksheets are included; one for land use change (LUC) and the other for land management change (LMC).
GTAP Data	Lists and summarizes GTAP source data
Modeling	Computes carbon & N_2O emissions from land use change
Domestic C-Factors	Derives carbon & N_2O intensity factors for domestic land use
C-Database	Contains aboveground carbon and belowground carbon data at a county level for the United States
International C-Factors	Derives carbon & N_2O intensity factors for international land use
Forest Land Area	Computes forest correction factor for shrubland transitions
International Conversion	Source data for international land conversions
International Reversion	Source data for international land reversions

Starting in 2018, new updates were incorporated in CCLUB to specifically estimate emissions associated with peatland loss in Southeast (SE) Asia and to aggregate international emission factors by area-weighted average. Section 7 explains the Intergovernmental Panel on Climate Change (IPCC)-based approach and data sources used in this CCLUB expansion. Temporal issues associated with modeling LUC emissions are the topic of Section 8. Finally, in Section 9 we provide a step-by-step guide to using CCLUB and obtaining results.

2. GTAP Data

CCLUB includes GTAP results from nine different biofuel production scenarios. Each scenario reflects a shock to the economy in response to an increase demand for a biofuels feedstock commodity. The first four scenarios were modeled in 2011 (Taheripour *et al.* 2011). The fifth scenario was modeled in 2013 (Taheripour and Tyner 2013). The sixth and seventh scenarios were derived from California Air Resources Board (CARB), while the last two scenarios were from recent GTAP simulations released in 2017 (see Chen *et al*., 2017 for more details on soy biodiesel simulations).

Table 2 lists the nine production scenarios and associated biofuels volumes. The cellulosic ethanol scenarios (stover, *Miscanthus*, switchgrass) are modeled in GTAP as incremental production volumes on top of corn ethanol production.

Table 2. Biofuels Scenarios Modeled in CCLUB

Case[1]	Case Description	Billion Gallons
A	An increase in corn ethanol production from its 2004 level (3.41 billion gallons [BG]) to 15 BG	11.59
E	An increase of ethanol from corn stover (i.e. AdvfE-Stover) by 9 BG, on top of 15 BG corn ethanol	9
F	An increase of ethanol from *Miscanthus* (i.e. AdvfE-Misc) by 7 BG, on top of 15 BG corn ethanol	7
G	An increase of ethanol from switchgrass (i.e. AdvfE-Swit) by 7 BG, on top of 15 BG corn ethanol	7
H	An increase in corn ethanol production from its 2004 level (3.41 BG) to 15 BG with GTAP recalibrated land transformation parameters	11.59
S1	Increase in soy biodiesel production by 0.812 BG (CARB case 8)	0.812
S2	Increase in soy biodiesel production by 0.812 BG (CARB average proxy)	0.812
S3	Increase in soy biodiesel production by 0.8 BG (GTAP 2004)	0.8
S4	Increase in soy biodiesel production by 0.5 BG (GTAP 2011)	0.5

[1]Note: Case classifications A, E, F, and G refer to Taheripour *et al.* (2011). Case classification H refers to Taheripour and Tyner (2013). Case classifications S1-4 refer to Taheripour *et al.* (2017) and Chen *et al.* (2017).

The 2013 GTAP scenario (case H) shocked the production of corn ethanol by the same volume as the 2011 Case A scenario. These two modeling exercises, however, differ in the treatment of two key aspects of the GTAP model. First, in 2011, GTAP included one land transformation elasticity for the globe. Land transformation elasticity is a parameter that reflects the ease of land transition from one state to another; a low value indicates limited land transitions. Taheripour and Tyner (2013) used two United Nations Food and Agriculture Organization (FAO) land cover datasets to develop region-specific land transformation elasticities that were used in the development of the 2013 GTAP results used in CCLUB. One dataset allows determination of changes in agricultural land area. Based on this dataset, the authors categorized GTAP regions (See Section 4) as having a low, medium, or high land transition elasticity. Taheripour and Tyner (2013) used the second dataset to characterize changes in harvested areas among crop types. They used it to develop land transformation elasticities among crops. The United States was characterized as having low rates of land transformation overall, but high transformation elasticity among crops. Taheripour and Tyner (2013) found that the United States moved a sizeable amount of agricultural land to produce corn and oilseed crops without significant expansion in overall agricultural land.

The second change in GTAP between the 2011 and 2013 modeling exercises is the treatment of the costs of converting pasture and forest to cropland. In 2011, the cost of conversion of both of these land types to cropland was identical. Taheripour and Tyner (2013) modified the land nesting structure in GTAP to reflect the greater cost of conversion of forest to cropland as compared to converting pasture to cropland that is generally observed in the real world. This change essentially makes it more costly to convert forest to cropland than in the 2011 GTAP version.

In 2017, four GTAP-based LUC results became available for soy biodiesel production in the United States. Depending on the case, the LUC matrices vary by GTAP versions and biofuel shocks. In particular, the CARB *case 8* and the CARB *average proxy* cases represent LUC results used by CARB. The former refers to the case 8 (of 30 cases) used by CARB, while the latter aims to proxy LUC for the 30-case average by using averaged GTAP parameters (See details in Chen *et al.*, 2017). In these two cases, GTAP used 2004 database, and did not consider land intensification (e.g., multiple cropping and/or returning unused cropland to crop production). In cases labeled "GTAP 2004" and "GTAP 2011", however, GTAP applied land intensification in both, and used the 2004 and 2011 database, respectively (Chen *et al.*, 2017).

GTAP permits three land types to be tapped for biofuel production: forest, grassland, and feedstock lands. The latter is agricultural land that has been converted to agriculture dominated by the production of biofuel feedstocks. In a differently nested category, the model also accesses a fourth land type: cropland-pasture. Figure 2 illustrates the land transitions considered in CCLUB.

In 2010 as we developed cases A – G (Table 2), we, along with collaborators at the University of Chicago, compared the GTAP land database with both the National Land Cover Datasets (NLCD), which are part of the USDA-National Agricultural Statistics Service (NASS) Cropland Data Layers (CDL), and the U.S. Forest Service's Forest Inventory data. We aimed to align forest area in the United States in our analysis with this database because we used Forest Service data to develop emission factors for aboveground and belowground carbon in addition to values for foregone sequestration. We therefore needed to reconcile forest area in the NLCD with forest area in GTAP.

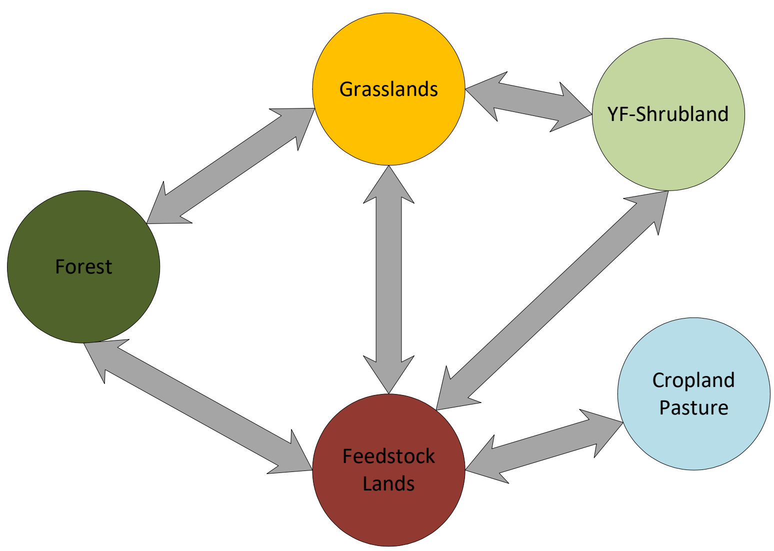

Figure 2. Land Transitions Modeled in CCLUB. Arrows indicate land use change directions.

The NLCD for 2006 put forest area at 207 million hectares (ha) for the lower 48 states. Including woody wetlands would bring this number up to 240 million ha. This figure is similar to the forest area from the U.S. Forest Service's Forest Inventory Data Online (FIDO) database of 254 million ha. If we add forested area in Alaska, the total forest area rises to 285 million ha. However, the GTAP database includes a significantly higher value (370 million ha) for total forested land than these other data sources (see Table 3).

Table 3. GTAP vs. CDL Forest Area Comparison

AEZ	CDL Forest Area (ha)	GTAP Forest Area (ha)	CDL Accessible Forest Area (ha) (CLD_a)	GTAP Accessible Forest Area (ha) ($GTAP_a$)	Proration Factor ($CDL_a/GTAP_a$)
7	47,405,654	8,565,128	4,916,174	3,855,223	1.28
8	17,272,038	16,811,112	3,249,339	7,568,672	0.43
9	10,321,261	10,603,159	4,877,404	4,774,257	1.02
10	57,660,896	68,714,584	38,053,673	51,625,425	0.74
11	49,317,712	56,696,608	41,537,500	41,732,227	1.00
12	48,740,427	69,617,736	41,543,291	53,074,258	0.78
13	10,325,263	17,098,376	2,860,066	7,697,724	0.37
14	24,624,059	61,735,484	10,557,947	27,793,441	0.38
15	18,497,217	55,407,136	9,066,574	24,948,026	0.36
16	780,733	5,180,770	361,713	2,332,297	0.16
Total	284,945,260	370,430,093	157,023,681	225,401,549	0.70

Of the total forest area in both the CDL and GTAP data, some is inaccessible for biofuel production (national and state forest) and the remainder is accessible. Purdue provided the total split between accessible and inaccessible forest land in GTAP with accessible forest land accounting for 225 million ha out of the 370 million total forest ha. Our analysis indicated that the GTAP database uses the methodology by Sohngen (2004) to derive accessible vs. inaccessible land ratios by agro-ecological zone (AEZ) and then applies these ratios to the GTAP forest areas by AEZ. The reproduced GTAP accessible forest land by AEZ is shown in Table 3. A map showing the distribution of AEZs in the United States is in Figure 3. In our CDL analysis, subtracting state and national forest areas from the CDL total forest area data yielded 157 million ha of accessible forest. Across most AEZs (but not all) this is substantially less accessible forest land than GTAP predicts.

Based on the differences in the amount of accessible forest lands estimated by GTAP and the CDL analysis we assume that some of the GTAP accessible forest land is shrubland rather than mature forest land. To address this issue and to be consistent with U.S. Forest Service data, we added young forest-shrubland (YF-Shrub) as a fifth land type. Shrubland is defined in the NLCD Classification as "areas characterized by natural or semi-natural woody vegetation with aerial stems, generally less than 6 meters tall." To determine the amount of land classified as YF-Shrub, we applied a proration factor to the accessible forest land GTAP predicted to be converted. The proration factor is calculated at the AEZ level as the ratio of accessible forest land in the CDL database to accessible forest land in the GTAP database (see Table 3). For example, if in a certain scenario GTAP predicted the conversion of 10,000 ha of forest to feedstock lands in AEZ 14, applying the proration factor results in CCLUB modeling 3,800 ha and 6,200 ha of forest and YF-Shrub lands being converted, respectively. In two AEZs, the proration factor exceeds one. In that case, our approach increases the amount of mature forest that is converted and effectively decreases the amount of YF-Shrub that converts to feedstock production land.

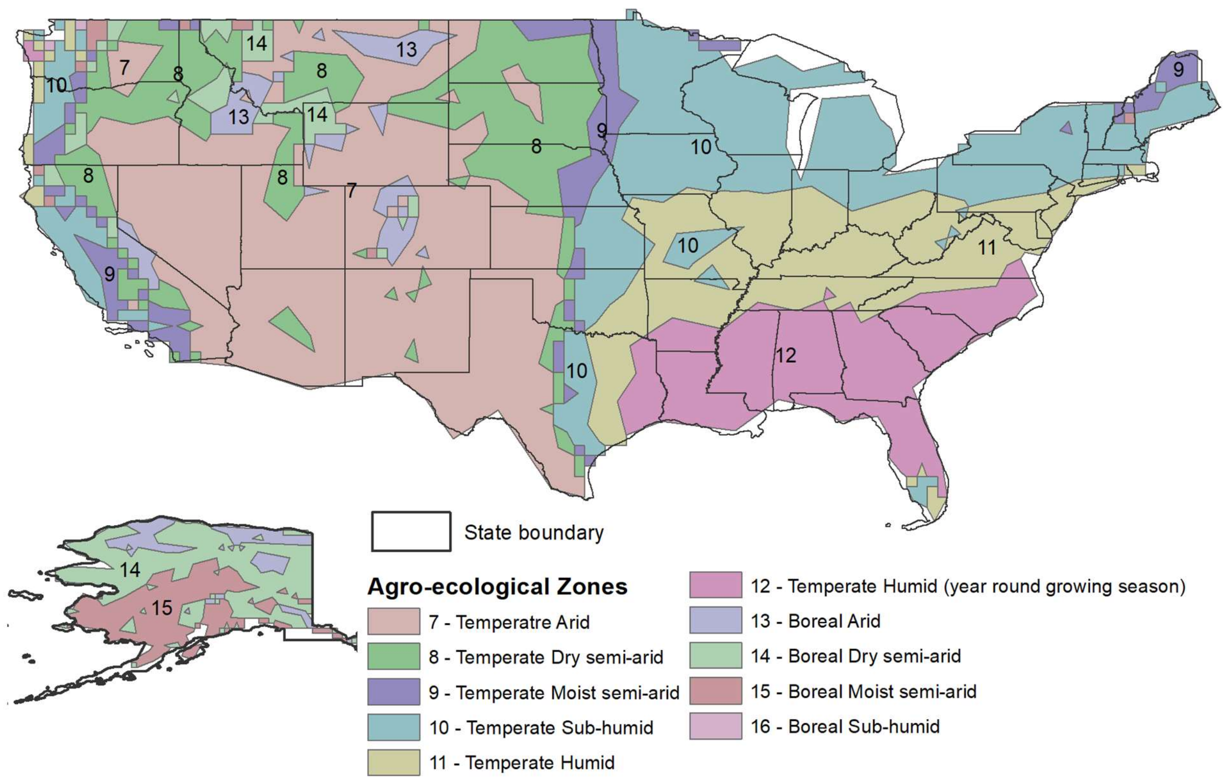

Figure 3. Distribution of AEZs in the United States. Data source: https://www.gtap.agecon.purdue.edu/resources/res_display.asp?RecordID=1900

Converting YF-Shrub lands will have a lower carbon penalty than converting mature, carbon-rich forests. We therefore modified mature forest carbon emission factors to reflect this difference. The modified forest emissions factor for YF-Shrub is based on the relative height of forest stands in each state compared to shrubland. The relative tree heights for each state were derived from Pflugmacher (2008) and Buis (2012) (see Appendix A).

3. Belowground Carbon Data for the United States

This work took advantage of a surrogate model for CENTURY's soil organic carbon (SOC) sub-model (SCSOC) developed by Kwon and Hudson (2010). Use of CENTURY to estimate soil C stock change was logical as it is well-developed for croplands, grasslands, and forests (Parton *et al.* 1987, Paustian *et al.* 1992, Kirschbaum and Paul 2002) and can simulate land transitions incorporated in the GTAP modeling framework. Recently, Kwon *et al*. (2017) further evaluated the accuracy and precision of SCSOC for estimating SOC sequestration under rainfed corn-based cropping systems in the US.

The SCSOC includes mass balance and decomposition kinetics equations for the three primary soil organic matter (SOM) pools (i.e., active, slow and passive SOM) described by CENTURY. Important differences between CENTURY and SCSOC are that SCSOC is coded and solved within the PROC MODEL of SAS (SAS Institute 2004) and decoupled from models of plant growth, nutrient cycling, and hydrologic processes described within CENTURY and associated variants. Use of the SCSOC provides the advantages of transparency and relative simplicity while allowing users to easily modify time-dependent CENTURY inputs. Important inputs to SCSOC include aboveground and belowground crop/plant C input rates to soil, and the site-specific decay rate coefficient of the SOM pools.

Overall, SOC modeling work in CCLUB builds on Kwon *et al.* (2013), in which the SCSOC model was used to derive emissions factors at the state level based on the scenarios that land presently in croplands, grasslands or pasture/hay (from this point on called grasslands), and forests could be converted to at least one of five likely biofuel feedstock production systems: corn-soy rotations, corn-corn rotations, or corn-corn rotations with stover harvest, switchgrass, and *Miscanthus*. To anticipate soil carbon emissions from agricultural lands set aside for conservation, croplands/conservation reserve modeling scenarios considered lands that had never been cropped (grasslands) and that had reverted to grasslands after a period of cropping.

The 2014 CCLUB release contained significant SOC modeling updates. First, two new feedstocks, poplar and willow, have been included. It is important to note that CCLUB does not generate LUC GHG emissions for biofuels produced from these feedstocks because no GTAP modeling exercises have been completed to reflect those scenarios. The SOC emissions factors in CCLUB for these two feedstocks can be used to estimate domestic GHG emissions associated with conversion of forest, cropland-pasture, cropland, and grassland to produce these feedstocks. Combining original land use, feedstock type, and land management practice resulted in 40 general LUC scenarios to consider for soil carbon emissions. The transitions are diagrammed in Figure 4 and presented in tabular format in Appendix B. The scenario numbers in Appendix B identify these scenarios within CCLUB.

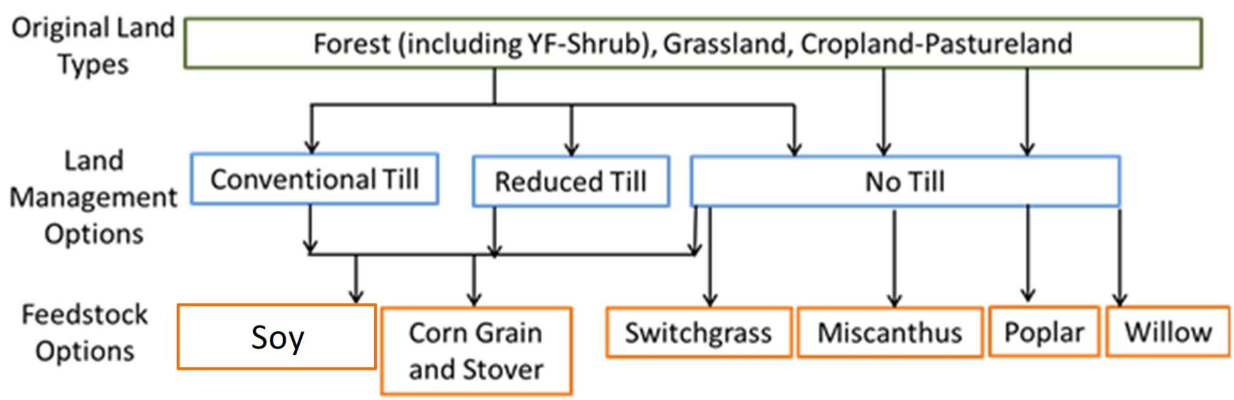

Figure 4. Soil Carbon LUC Scenarios Modeled in CCLUB

The second significant update to CCLUB in 2014 was that SOC results for a soil depth of 100 cm have been added. We expanded CCLUB to include these results because, although most farming activity directly disturbs soils to 30 cm, SOC changes at 100 cm can still occur and influence the overall SOC implications of LUC (Qin *et al.* 2016a). CCLUB still contains results for SOC changes at 30 cm. As with previous releases, all modeling results are at the county level. For this analysis, inputs to the SCSOC model include county-level edaphic characteristics, climate data, and biomass estimates. We identified the most prevalent land use categories present within each county using remote sensing analysis of the NLCD 2006 reported by Fry *et al.* (2011). Then we identified soil texture classes (e.g. sand, clay, and loam) of the Harmonized World Soil

Database (HWSD) within each land use category. The monthly temperature and precipitation data used to calculate the effects of weather were from weather station data between 1960 and 2010 reorganized to the county level.

All SOC modeling scenarios include the effects of erosion. They use the average soil loss or erosion rates (Mg soil ha^{-1} yr^{-1}) for croplands and pasture/hay/grasslands were obtained from the National Resources Inventory (NRI) erosion estimates (USDA-NRCS), which are based upon the Universal Soil Loss Equation and Wind Erosion Equation (for wind erosion), by averaging periodic erosion estimates from 1982, 1987, 1992, 1997, 2002, and 2007. For forests and land used for either switchgrass or *Miscanthus*, we assumed zero soil erosion rates. Under a no-erosion scenario, we assumed zero soil erosion rates for the croplands and pasture/hay/grasslands as well.

It is important to note that the soil carbon decay coefficients in CENTURY for corn agriculture were adjusted from default values because several studies have shown that CENTURY soil decay coefficients need to be adjusted upward to properly estimate soil organic carbon (SOC) levels under row-cropped systems (Carvalho Leite *et al.* 2004; Matthews and Pilbeam 2005). Dunn *et al.* (2013) reported the influence of using the calibrated value of this parameter and the inclusion of erosion in SOC modeling on LUC GHG emissions.

CCLUB includes two basic yield scenarios: a constant yield and a yield increase scenario. Note that GTAP simulations did not incorporate crop yield increases for any of the feedstocks. To estimate the yields for major crops (i.e. corn, soybean, and wheat), we used the historical records of crop yields surveyed by USDA-NASS accessed through QuickStats. Eaton of Oak Ridge National Laboratory provided county-level yields of switchgrass, *Miscanthus*, and poplar based on PRISM-EM modeling (Eaton 2014). Yields of these feedstocks were calculated in a consistent manner with the methods used in the Billion-Ton Study (U.S. Department of Energy 2011). To estimate corn yields for the corn-corn scenarios, we used state-level corn yield records during the early agricultural period (1880 – 1950) and county-level corn yield records for the modern agricultural period (1951 – 2010) (Appendix B). All the records were obtained from USDA-NASS QuickStats. Future corn yield assumptions (2011-2040) included a constant yield case based on the 20 yr-average of county-level corn yields (1991 – 2010) and a yield increase case based on a simple regression equation derived from each county's corn yield records of modern agricultural period (Kwon *et al.* 2013). It was assumed that the harvest index (ratio of stover to corn grain) and the root-to-shoot ratio would be constant into the future. This method is consistent with the approach used by Miranowski *et al.* (2011) who used linear regression to predict yield trends although on a state level. For some counties, insufficient corn yield data were available to generate results. At this time, CCLUB does not include results for these counties. The yield increases for *Miscanthus* and switchgrass were projected to be 1% annually, which is more conservative than the recent update of the Billion-Ton Study (U.S. Department of Energy 2011), which considered annual yield increases of 2%, 3%, and 4%.

Corn-based systems were simulated with three different tillage options [i.e., conventional tillage (CT), reduced tillage (RT), and no tillage (NT)] while the two perennial grass systems were simulated with NT. Under CT, 95% surface residue is assumed to be mixed to soils, under RT, 70% is mixed to soils, and under NT, 5% is mixed to soils. Stover harvest rates were set at 30% to avoid increasing soil erosion or diminishing soil fertility (Nelson 2002; Wilhelm *et al.* 2004; Johnson *et al.* 2006; Simon *et al.* 2010a). To leave similar amounts of aboveground residues in place and thus avoid soil depletion, a 90% biomass harvest rate was used for switchgrass and *Miscanthus* (Eaton 2014). Table 4 summarizes key modeling parameters for each feedstock.

Table 4. Key Parameters Used in the SCSOC Model for Corn, Switchgrass, *Miscanthus*, Poplar and Willow.

	HI[1]		RS[2]	Aboveground biomass return[3]	TILL[4]
	1880-1950	1951-2040			
Corn	0.35	0.53	0.55	0.7, 1.0	NT, RT, CT
Switchgrass			1.00	0.1	NT
Miscanthus			1.00	0.1	NT
Poplar			2.00	0.1	NT
Willow			2.00	0.1	NT

[1]HI, harvest index for historical (1880-1950) and modern (1951-2040) land use periods (Vetsch & Randall; Allmaras *et al.*, 1998; Prince *et al.*, 2001; Halvorson *et al.*, 2002; Pedersen *et al.*, 2004). [2]RS, root to shoot ratio (Buyanovsky & Wagner, 1986; Ojima *et al.*, 1994; Dohleman, 2009; Garten Jr. *et al.*, 2010; Pacaldo *et al.*, 2013; Garten Jr. *et al.*, 2011); for poplar and willow, the root includes total belowground biomass and aboveground stool. [3]Return rate for aboveground biomass (Kwon *et al.*, 2013; Eaton, 2014); for corn, the aboveground biomass return rate has two options in the model. [4]TILL, tillage options in the model (Kwon *et al.*, 2013). Most parameters for corn, switchgrass and *Miscanthus* were inherited from the previous version of SCSOC (Kwon *et al.*, 2013).

For ethanol LUC scenarios, CCLUB users can model SOC changes at the county level resulting from the land transitions in Figure 4 at either a 30 cm or 100 cm soil depth and with or without yield increase. In this version of CCLUB, users can select an option to calculate SOC changes at a national level using area weighting based on the share of corn planted area using different types of tillage. Our baseline uses the US Average tillage that assumes 34% residue left on the soil surface (USDA, 2015) and CCLUB's assumptions about the amount of residue associated with NT, RT and CT practices (Table 5). The latter differs from USDA's Agricultural Resource Management Survey (ARMS) (USDA, 2015) which reports the share of corn planted area and the amount of residue left on the soil surface after planting for four tillage types (no till, mulch till, reduced, or conventional tillage). We allocated less area to no till because the percent of residue remaining after planting is higher in CCLUB (95%) than in ARMS (65%); and assume a larger share of land is under RT, which would include land with mulch till. Because CCLUB and ARMS assumptions about residue coverage are quite similar, the area assumed to be under that practice is the same (25%). In future CCLUB releases, we may use ARMS' tillage type definitions to avoid any confusion caused to users.

Table 5. Comparison of Tillage Systems in USDA's ARMS and CCLUB. The ARMS data is derived from tailored report of corn residue management practices in 2010.

	ARMS		CCLUB	
Tillage System	Residue remaining after planting (%)	Share of corn planted area (%)	Residue remaining after planting (%)	Share of corn planted area (%)[1]
No Till	65	24	95	16
Mulch Till	41	28		
Reduced Tillage	22	23	30	59
Conventional Tillage	8	25	5	25
US Average	**34**	**100**	**34**	**100**

1. Estimated by assuming that conventional tillage in both ARMS and CCLUB is comparable, although there is a 3% of difference for residue remaining after planting.

For soy biodiesel LUC, current CCLUB has only included SOC results for 100 cm soil depth under yield increase scenario. In CCLUB, county-level SOC changes are grouped by AEZs then averaged to provide the value for a given scenario in that AEZ. For land converted to corn production, we develop an optional area-weighted AEZ-level average SOC change based upon county-level average harvested areas in corn over 5 years (2006-2010). In future CCLUB releases, we may use an area-weighted average or other weighting approaches for other feedstocks.

Alternatively, CCLUB can be parameterized with domestic emissions factor sets from the Woods Hole Research Center, which was originally authored by R. Houghton and provided to the California Air Resources Board and GTAP in support of land use modeling efforts, or from Winrock (Harris *et al.* 2009). The Woods Hole emissions factor dataset is reproduced in Tyner (2010). Woods Hole factors are not available by AEZ but are at the biome level. Winrock provides carbon stock data at the state level; the average of these values is used in CCLUB.

4. Non-soil Carbon Data for the United States

Non-soil carbon from forest ecosystem conversions is based on COLE (Van Deusen and Heath 2010, Van Deusen and Heath 2013). In order to determine non-soil carbon impacts of forest-to-cropland conversion scenarios we accessed the county-by-county data for the five different non-soil components: aboveground live tree carbon density, aboveground dead tree carbon density, understory carbon density, forest floor carbon density, and coarse woody debris carbon density.

Foregone sequestration from annual biomass growth is based on the COLE value for net annual growth. In time, some feedstock production land may revert back to forest land. Reversion non-soil carbon factors are also based on COLE's net annual growth. The emissions/sequestration effects from root biomass are included in the boundary of the SCSOC modeling runs. It is important to note that this approach provides consistency of data sources throughout CCLUB: the spatially explicit US Forest Service COLE data is used for aboveground carbon stocks, the corresponding root biomass values (corresponding to the aboveground carbon values) are used to parameterize SCSOC, and finally the predicted GTAP transitions are adjusted to match the US Forest Service forest area (via the forest proration factor described in Section 2).

The carbon in some harvested wood will not be emitted, but contained within harvested wood products (HWP) in productive uses such as buildings. Based on Heath *et al.* (1996) and a follow-up conversion with Heath we determined that 60% of the combined aboveground live and dead tree carbon density can be removed from the forest. 35% of this carbon is stored in products and an additional 35% is converted into useful energy (both considered harvested wood product offsets). The carbon in the remaining aboveground categories is assumed to be released to the atmosphere as is carbon in the waste wood. Figure 5 depicts the fates of aboveground live and dead tree carbon based upon Heath *et al.* (1996). Alternatively, the CCLUB user has the option to exclude any HWP offsets (HWP set to zero).

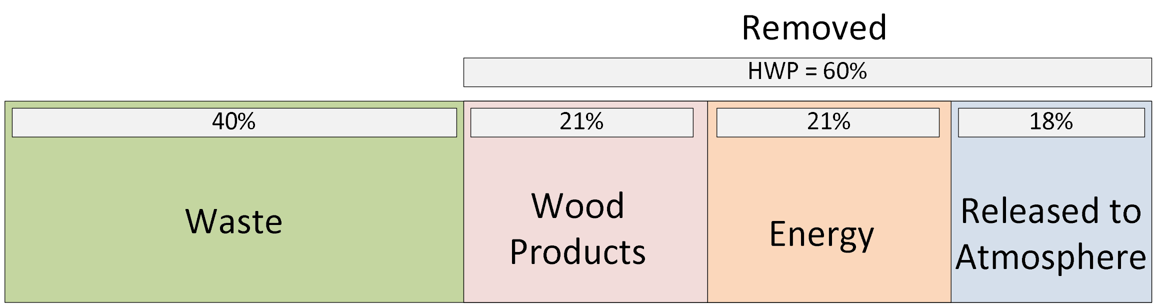

Figure 5. Fate of Aboveground Live and Dead Tree Carbon

For the emissions assessments based on the Woods Hole dataset (Domestic and International), the amount of aboveground carbon emitted to the atmosphere is 75%. CCLUB users can adjust this factor in the respective sections of the Domestic C-Factors and International C-Factors worksheet (in the column titled “C Released During Conversion”). Winrock, in developing their carbon stock values, assumed no carbon is sequestered in HWP (Harris *et al.* 2009).

All GTAP results are based on AEZs. We therefore aggregated the higher resolution county-level factors to match the AEZ regions. AEZ-level factors were derived as average of county-level factors. As with the belowground carbon county-level to AEZ aggregation, we may use different aggregation techniques in future CCLUB releases.

5. International Carbon Emission Factors

The primary international carbon emissions assessment in CCLUB is based on carbon content data for international lands obtained from Winrock International (Harris *et al.* 2009). These data were developed for US EPA’s Renewable Fuel Standard (RFS) and accompanying analysis of life-cycle GHG emissions of biofuels, including from LUC. CCLUB uses the modifications to the Winrock factors that EPA adopted in modifying their analysis between the proposed and final versions of RFS2.

Winrock used recent land cover products derived from satellite imagery and other data sources and developed GHG emission factors for various land cover conversions. They report one emission factor per country, and for some countries for administrative units, over a 30-year time period. This time period matches the time horizon used to develop domestic emission factors as described in Section 3. The Winrock 30-year emission factors are calculated with emission factors developed for three different periods following the land transition as described in Equation 1.

$$EF_{30} = EF_1 + 19 \times EF_{2-19} + 10 \times EF_{20-8} \qquad [1]$$

where

EF_{30} = GHG emissions 30 years after the transition [Mg CO_2e/ha];

EF_1 = GHG emissions in the first year after the transition [Mg CO_2e/ha];

EF_{2-19} = GHG emissions in years 2 through 19 after the transition [Mg CO_2e/ha]; and

EF_{20-80} = GHG emissions in years 20 through 80 after the transition [Mg CO_2e/ha].

Complete details of the development of the Winrock emission factors are contained in Harris *et al.* (2009) but we summarize a few salient points in Table 6.

In the Winrock data set, with the exception of reversion to forests, reversion emission factors are estimated as the reverse of emission factors with all biomass carbon stock increases occurring in the first year after reversion. Soil carbon stock changes on abandoned cropland, however, take 20 years to reach pre-conversion values.

In the case of croplands that revert to forests, biomass accumulates annually over the 30-year reversion period. To be conservative, Winrock assumed that the newly growing trees accumulate carbon at the foregone sequestration rate. In reality, these young trees would incorporate carbon at a faster rate than the trees in more established forests that may have been cleared for feedstock production. Further details on these calculations are available in Harris *et al.* (2009).

The Winrock data set does include estimates of uncertainty for these emission factors, which we may include in a future release of CCLUB.

To incorporate these emission factors into CCLUB, we combined emission factors for countries that are included in the categories in which GTAP results are reported. Table 7 lists these categories and the countries that are included in each. We used a land area-weighted average of the emission factors for these countries. We included original Winrock datasets at regional/ administrative unit level under "Land Conversion Emissions Factor Data Inputs (Winrock)". 30-

yr emission factors are estimated based on Winrock data and other data sources including updated IPCC report (IPCC, 2014).

For LUC associated with peatland loss in SE Asia (Mala_Indo in GTAP, including Malaysia and Indonesia), the GHG emissions are specifically estimated to account for CO_2, CH_4 and N_2O emissions related to peat loss and biomass change (loss or growth). In CCLUB, the users may choose to use either arithmetic mean or area-weighted average in calculating international emission factors. A detailed report will be released separately to document emissions from LUC associated with peat loss in SE Asia (Qin and Kwon, 2018).

Table 6. Data Sources and Key Methodology Points for Winrock Emission Factors

Land Type	Forest	Grassland	Cropland Pasture[2]
Data source	Figure 3 in Harris *et al.* (2009) shows a world map color-coded to indicate the data source for each region.	Data for Brazilian grasslands based on a number of data sources. For all other countries, estimates based on Table 6.4 of the IPCC AFOLU[1] Guidelines	Calculated as the average of forest, shrubland, grassland, and cropland carbon stocks.
Key methodology points	Includes CH_4 and N_2O emissions from forests cleared by burning. No carbon is assumed to be sequestered in harvested wood products. Foregone sequestration is included based on several literature reports.	Outside of Brazil, ratios of savanna and shrubland areas were calculated from grasslands based on the ratios of areas of these land types from the Brazilian data set	Follows International Geosphere-Biosphere Programme (IGBP) land cover definitions

2. Agriculture, Forestry, and Other Land Use. Available at: http://www.ipcc-nggip.iges.or.jp/public/2006gl/vol4.html
3. CCLUB assigns emission factors the "Mixed" category from Winrock, which consists of a crop and vegetation mosaic, to international cropland pasture areas undergoing LUC as predicted by GTAP.

CCLUB also includes the Woods Hole data set. Users can select either the Winrock or Woods Hole data set to estimate international LUC GHG emissions.

Table 7. Aggregation of Countries in Winrock Data Set to GTAP Regions. An asterisk indicates subregions of the country were included in the average.

Region	GTAP Code	Countries Included
United States[1]	US	United States*
European Union	EU 27	Austria, Belgium, Bulgaria, Cyprus, Czech Republic, Denmark, Germany, Spain, Estonia, Finland, France, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Netherlands, Poland, Portugal, Slovenia, Romania, Slovakia, Sweden, United Kingdom
Brazil	Brazil	Brazil*
Canada	Canada	Canada*
Japan	Japan	Japan
China	CHIHKG	China*
India	India	India*
Central America	C_C_Amer	Belize, Costa Rica, Ecuador, El Salvador, Guatemala, Honduras, Mexico*, Nicaragua
South America	S_o_Amer	Colombia, Argentina*, Bolivia, Chile, Paraguay*, Peru, Uruguay, Venezuela
East Asia	E_Asia	North Korea, Mongolia, South Korea, Taiwan
Malaysia and Indonesia	Mala_Indo	Indonesia*, Malaysia*
Rest of Southeast Asia	R_SE_Asia	Philippines*, Singapore, Thailand*, Vietnam*
Rest of South Asia	R_S_Asia	Bangladesh, Cambodia, Pakistan, Sri Lanka
Russia	Russia	Russia*
Other Eastern Europe and Rest of Former Soviet Union	Oth_CEE_CIS	Albania, Armenia, Azerbaijan, Belarus, Bosnia and Herzegovina, Croatia, Kazakhstan, Kyrgyzstan, Tajikistan, Turkey, Turkmenistan, Uzbekistan
Middle East and North Africa	MEAS_NAfr	Afghanistan, Algeria, Egypt, Ethiopia, Iran*, Iraq, Israel, Liberia, Libya, Morocco, Oman, Saudi Arabia, Tunisia
Sub Saharan Africa	S_S_AFR	Angola, Botswana, Cameroon, Central African Republic, Democratic Republic of the Congo, Ghana, Guinea, Kenya, Madagascar, Malawi, Mozambique, Namibia, Nepal, Nigeria*, Senegal, Somalia, South Africa*, Tanzania, Togo, Uganda, Zambia, Zimbabwe

1. Winrock data for the U.S. are only used in CCLUB if the user selects that data set for the domestic emissions modeling scenario.

6. Domestic Carbon Emissions from Land Management Change

Land management change is included as an option for corn stover ethanol to calculate carbon emissions associated with agricultural management practices including cover crop adoption and manure application and varying levels of tillage and corn stover removal. An technical report documents the data, methodology, and assumptions behind the incorporation of land management practices in corn-soybean systems with varying levels of stover removal in the GREET model and its CCLUB module (Qin *et al.*, 2015). The resulting SOC changes under these various land management practices were incorporated into CCLUB and GREET was expanded to include energy and material consumption associated with cover crop adoption and manure application (Qin *et al.*, 2015).

7. Domestic and International CH_4 & N_2O emissions

In 2016, CCLUB was expanded to estimate CH_4 & N_2O emissions from international and domestic LUC at the AEZ level using the approach recommended by IPCC (2006). CH_4 emissions are mostly caused by biomass burning, especially in countries using fire as a method to clear land. In general, LUC can cause N_2O emissions through many routes (IPCC 2006), two of which are included in CCLUB. First, if land is cleared by burning during LUC, this burning emits N_2O. Secondly, LUC can cause organic matter loss in soil, which releases N_2O directly and indirectly. We treat these N_2O sources differently for domestic and international LUC as subsequently described.

Additionally, N_2O can be emitted from lands that are put into agriculture when fertilizer is applied to these lands and undergoes volatilization, leaching and runoff. In addition, agricultural residues decaying on land in agriculture will emit N_2O. In the case of N_2O emissions from fertilizer use and crop residue decay on land in agriculture, these emissions are accounted for through attribution to the biofuel feedstock in the main GREET model and are not accounted for in CCLUB. Figure 6 describes the sources of N_2O emissions as included in GREET and CCLUB for biofuel feedstocks.

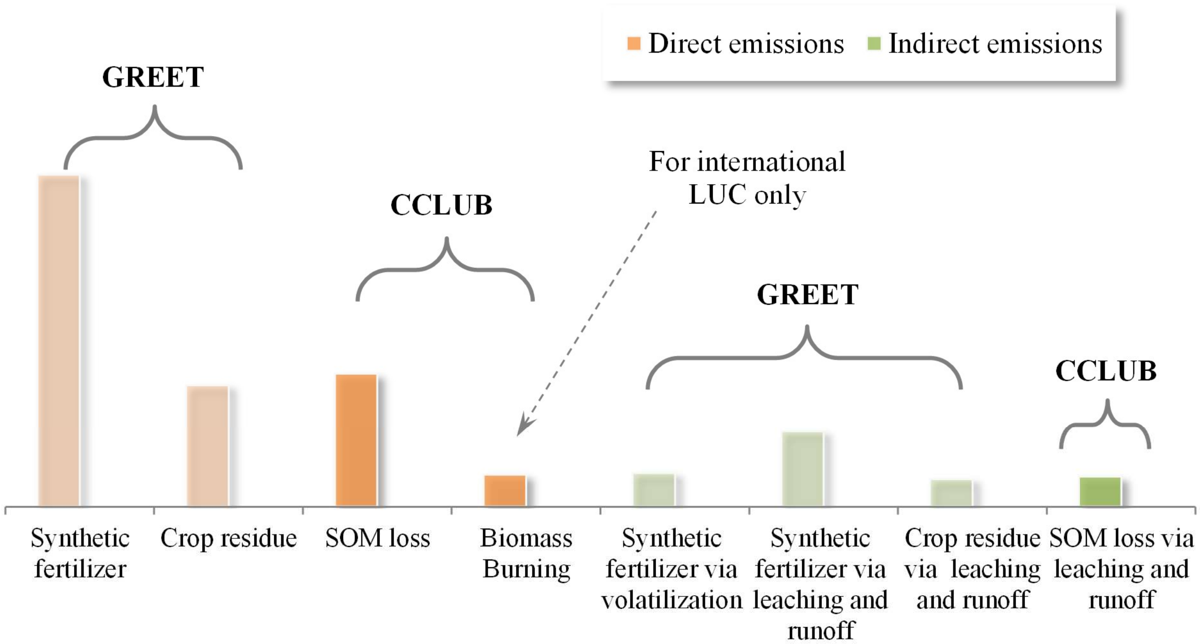

Figure 6. An example showing direct and indirect N_2O emissions from different N sources included in CCLUB and GREET. Biomass burning is for international LUC only.

In the case of N_2O emissions from biomass burning during land clearing, because biomass burning is uncommon in the United States (Harris *et al.*, 2009), we set domestic N_2O as zero (*Note*: users can modify this by change inputs in CCLUB *modeling* worksheet). However, CCLUB users have the option to include this N_2O emission source for international lands if they would like to do so. International N_2O emissions from biomass burning are either based on biomass production (dry matter) (forest and grassland) estimated by Woods Hole and IPCC emissions factors or Winrock N_2O emission factors. For Woods Hole and IPCC method, the default carbon content of wood (0.5 g C/g dry matter) and herbaceous grass (0.47 g C/g dry matter) are used to calculate biomass production from existing national biomass carbon stocks (IPCC, 2006). To choose IPCC N_2O emission factors for biomas burning, the major vegetation category (e.g., tropical, temperate and boreal) are classified based on dominant GTAP AEZ-level forest or grassland LUC area (see "Conversion Factors" in CCLUB). For the Winrock method, CCLUB includes the existing N_2O emissions estimated for countries clear land by burning. Also, CCLUB follows the Winrock method to account for CH_4 emissions for certain countries with biomass burning.

To estimate N_2O emissions from changes in SOM in mineral soils, it is necessary to have an estimation of SOC loss. Three data sources can be used as sources for SOC loss: SCSOC modeling results that are included in CCLUB (U.S. domestic only), Winrock (both domestic and international) and Woods Hole (both domestic and international). Change in SOC upon domestic LUC can be estimated by one of these options:

(1) SCSOC: using AEZ-level SOC loss estimated by SCSOC;

(2) Winrock: using Winrock estimated SOC loss at national-level;

(3) Woods Hole: using national-level SOC loss estimated from biome level Woods Hole factors.

To estimate international LUC-induced N_2O emissions from changes in SOC levels Winrock and Woods Hole international SOC loss data sets are the primary resources. For N_2O emissions from SOM loss, the IPCC default emission factor of 0.01225 (0.01 for direct emissions and 0.30×0.0075 for indirect emissions due to leaching/runoff) is used for both domestic and international LUC.

For both domestic and international LUC-induced N_2O emissions estimates, the soil organic matter C:N ratio (default value: 15) is used to calculate soil nitrogen change from SOC loss (IPCC, 2006).

For peat conversions in SE Asia, the N_2O emission factor of 1.5 t CO_2e ha^{-1} yr^{-1} for peatlands managed for extraction was adopted from IPCC (2014).

In accordance with GREET, the new global warming potential (GWP) value relative to CO_2 (IPCC AR5) used for CH_4 and N_2O are 28 and 265, respectively. This change has been applied in CCLUB to modify Winrock datasets.

8. Temporal Issues in Modeling LUC Emissions

CCLUB's assessment of carbon emissions from LUC depends on two critical time horizons: the duration of biofuels production and the emissions amortization period. Assumptions regarding the duration of biofuels production impact foregone sequestration from annual biomass growth and the associated soil carbon adjustments. Since the data set on soil carbon adjustments from the SCSOC model and the Winrock international carbon emission factors are based on 30-year equilibrium values, the production duration should not be varied significantly from that value. We assume that a relatively small variation of ±5 years may not introduce significant errors. The emissions amortization period refers to the duration over which a biofuels policy is analyzed.

9. Using CCLUB

In this section, we explain the contents of the eight sheets that make up CCLUB. We describe them in order of calculation flow rather than the left-to-right progression of sheets.

9.1. Overview Worksheet

This sheet contains author information and a list of worksheets and their descriptions.

9.2. Scenario and Results Worksheets

There are two worksheets including scenario and results, one is for LUC and the other for LMC. Below we show an example of how to use LUC worksheet. The use of the LMC worksheet is similar.

The *LUC Scenario & Results* sheet contains user inputs and a results section. Users select input values in the rose-colored cells. All options are visible in the yellow cells in each section. The first user input (Input 1) is the feedstock-to-fuel pathway. The user can choose from among the biofuel scenarios in Table **2** of this document, which include corn and cellulosic ethanol (corn stover, *Miscanthus*, or switchgrass feedstocks), and soy biodiesel options.

The second user input is the scenario selection for domestic carbon emissions scenarios (Input 2a). The data underpinning these scenarios is described in Sections 3 and 4. If the user opts to include domestic SOC emission factors from SCSOC modeling, he or she must choose whether to use modeling results that take into account yield increases (Input 2b) and select a soil depth (30 or 100 cm) as Input 2d. The land management practice options that constitute Input 2c allow the user to assess the influence of tillage practice on the results for corn and corn stover pathways. Input 2e allows users to identify which method to use for domestic N_2O emissions estimates (see Section 7). For input 3a, users choose between Winrock and Woods Hole data sets for international LUC emissions (Input 3a) including both carbon (Section 5) and CH_4/N_2O emissions (Section 7). In particular, when Winrock is chosen as the source, one can navigate to input 3b to determine the percentage of palm expansion on peat forest (SE Asia), with “0%” assuming no expansion on peat forest and “22%” being the latest updates (Qin and Kwon, 2018).

The user selects an HWP scenario for Input 4, either using the assumptions of Heath *et al.* (1996) or assuming all aboveground carbon is emitted when forests are converted to biofuel feedstock production.

In Input 5, users can indicate whether to include biomass burning for initial land clearing in international LUC. Answer “No” indicates no burning for all countries, and “Yes” for burning in all international countries only when “CENTURY SOC” or “Woods Hole” is selected in Input 2e. If Input 2e selects “Winrock”, then “Yes” indicates burning in countries biomass burning is a common practice based on Winrock estimates (Harris *et al.*, 2009).

In developing CCLUB, we modified GTAP data for area of converted forest as described in Section 2. Input 6 allows CCLUB users to adopt adjustments to converted forest lands by selecting “Yes” or to use raw GTAP data by selecting “No”. Input 7 allows users to choose approach for spatial average in both domestic (Section 3) and international LUC factors (Setion 5).

Users can alter the foregone carbon sequestration period by adjusting Input 8. Users are cautioned, however, that the modeling runs that produced domestic soil carbon values and Winrock emission factors are based on 30 year time horizons. Choosing values outside that time window may produce inaccurate results.

Finally, users can alter the amortization period in Input 9. See Section 6 for a discussion of how amortization influences results.

Once all inputs are selected, the user can click on the “Run Simulation” button and view results within CCLUB as described in the following paragraph. If the user also clicks on “Copy to GREET,” inputs and results will be transferred to GREET and incorporated into overall biofuel life cycle analysis. The user will have an active GREET spreadsheet after clicking this button.

No input or adjustments are required on other sheets to see the results, which vary based on the user selection in the Inputs section. Emissions are divided into land types of forest, grassland, cropland-pasture, and young forest-shrub. Note that Woods Hole data does not include the latter two land types. Just to the right of the main results table, results are tabulated for all data set options within CCLUB. In this section, the emissions are divided into domestic and international emissions, each of which are broken out as follows by land type (carbon emissions as an example):

- Domestic or international Emissions (Mg C): Total carbon emissions for the selected scenario by land type
- Domestic or international Emissions (Mg CO_2e): The total carbon emissions are converted to carbon dioxide equivalent emissions (3.67 g CO_2/g C)
- Domestic or international Annualized Emissions (Mg CO_2e/yr): The total carbon dioxide emissions are divided by the amortization period specified in Input 7
- Domestic or international Annualized Emissions (g CO_2e/gal): The annualized emissions are divided by the annual fuel production volume
- Domestic or international Annualized Emissions (g CO_2e/MJ): The volume-based emissions are converted to a unit energy basis with the lower heating value of ethanol.

The red highlighted box in the Results section contains the total carbon, N_2O & CH_4 or total GHG emissions associated with the selected scenario in units of g CO_2e/MJ.

9.3. GTAP Data Worksheet

This worksheet contains three sections. The bottom section with a heading of "GTAP Source Data Tables" contains the raw GTAP data generated as described in Section 2. The data are grouped by scenario. The section above the raw data, entitled "Land Use Summary by Region and AEZ" selects the LUC data from the appropriate scenario. The top section, "Land Use Summary by Region," contains the total of LUC by land type and country/region. These values are multiplied by the appropriate emission factors to generate LUC emissions results.

9.4. C-Database Worksheet

In this worksheet, soil organic carbon change data from the CENTURY model (SCSOC) are included for every scenario at the county-level. As described above, for some counties it was not possible to estimate SOC changes. County-level COLE data for aboveground carbon are also included in this worksheet to the right of county-level SOC data. SOC and aboveground carbon for each county is averaged by AEZ in the table at the top of the worksheet for use on the Domestic C-Factors worksheet.

It is important to note the sign convention for this worksheet. SCSOC results are included as the change in soil carbon stock for each county. If SOC in the land's final state is greater than in its initial state, the SOC change will be positive. In this case, biofuel feedstock production has benefited SOC. If the land transition results in a decrease in SOC, SOC has been depleted as a result of the land transition and the SOC change will be negative.

9.5. Domestic C-Factors Worksheet

This worksheet displays the Domestic factors based on CENTURY/COLE and the Domestic factors based on Winrock and Woods Hole. This sheet uses color coding to guide the user's eye. Soil and non-soil carbon stock changes are red- and blue-highlighted, respectively. Annual growth values are green-highlighted.

The first table contains soil carbon stock changes by AEZ as modeled in CENTURY and described in Section 3. Separate tables are provided for each scenario option in Input 2.

The second table contains non-soil carbon by AEZ, developed as explained in Section 4. Note that only aboveground carbon emission impacts of forest conversion are considered because belowground carbon stock changes (from soil and tree roots) are considered in SCSOC. In this table, the YF-Shrub correction factor described in Section 2 is also calculated.

The third table contains data from COLE for total net tree growth. The values stated in Mg carbon per hectare per year are calculated from the carbon contained in that new tree growth using a forest carbon factor of 50%, which is consistent with the IPCC Good Practice Guidance For Land Use, Land Use Change and Forestry (IPCC, 2003).

Section B and Section C of this sheet contains the Woods Hole and the Winrock Domestic emissions factors, respectively and calculates emission factors.

9.6. International C-Factors Worksheet

This sheet has the same color scheme as the Domestic C-Factors sheet. It calculates International emissions factors from the Winrock and Woods Hole data sets, which are described in Section 5.

9.7. Forest Land Area Worksheet

Section A of this sheet contains state-level land use data from CDL analysis that is mapped to the AEZ level using the matrix displayed in Section B. Forest proration factor calculations are in Section C of the sheet. Section 2 of this document discusses these calculations.

9.8. Modeling Worksheet

At the top of this sheet, conventions used in calculations are defined. Carbon emission and sequestration factors are defined as positive and negative, respectively. Converted land areas are treated as negative whereas reverted lands are defined as positive. The color coding of the spreadsheet is also defined. Soil and non-soil emissions factors are highlighted in red and blue, respectively. The annual growth of forests is highlighted in green. Land areas imported from other tabs are colored gray.

The first data section A1 in the sheet contains domestic emissions (both CO_2 and N_2O) based on data from the SCSOC modeling effort described in Section 3. Modeling is grouped as follows. First emissions factors for conversion and reversions of forests, grasslands, YF-shrublands, and cropland-pasture lands (as Figure 2 depicts) are calculated as the sum of aboveground carbon, soil carbon, and foregone sequestration from annual growth. Note that the soil carbon emissions factors for the corn ethanol, stover ethanol and soy biodiesel scenarios are dependent on the selected tillage scenario (CT, RT and NT). In a second step those emissions factors are matched to the selected biofuels scenario and multiplied by the corresponding GTAP land area changes for each transition. It is in this sheet that the forest proration factor is applied.

Domestic emissions calculated with Woods Hole and Winrock emissions factors are also displayed in this sheet in Sections A.2 and A.3.

The international components of the Woods Hole and Winrock emissions factor data dataset described above are used to assess international emissions for the selected biofuels scenarios in Sections B1 and B2.

All carbon emissions are included in subsection *a* while N_2O emission are in subsection *b*.

9.9. Selected Results and Outstanding Issues

The results for one likely parameterization scenario of CCLUB are shown in Table 8. In this scenario we have selected CENTURY (SCSOC)-based soil carbon factors reflective of projected yield increases and a 100 cm modeled soil depth combined with aboveground carbon factors based on U.S. Forest Service COLE data. Furthermore, for domestic emissions we have adjusted the GTAP results with YF-Shrub transitions. We have included HWP factors based on Heath *et al* (1996). International emissions were calculated with the Winrock data set. 22% of palm expansion to non-existing cropland was assumed on peat forest in the SE Asia (Qin and Kwon, 2018). For ethanol, the chosen scenario would indicate that ethanol production from corn stover and switchgrass would not result in any significant LUC GHG emissions. If *Miscanthus* is the selected ethanol feedstock, LUC results in net carbon sequestration. Corn ethanol production would result in net positive LUC GHG emissions (with less emissions under no-till management). Dunn *et al.* (2013) explored how results vary with different modeling options, but used the state-level SOC emission factors that the 2012 version of CCLUB contained. Qin *et al.* (2016b) further investigated how spatially-dependent soil carbon emission factors can influence life-cycle GHG emissions using county-level SOC emission factors in CCLUB 2015 version. N_2O emissions associated with SOM loss were included since the CCLUB 2016 version. Table 8 also includes results using GTAP results from Taheripour and Tyner (2013) that used the refined GTAP version as described in Section 2. Using this version of GTAP reduced corn LUC GHG emissions by 4 g CO_2e/MJ. For soy biodiesel, the GHG emissions vary by LUC scenarios. Chen *et al.* (2017) further discussed LUC impacts on soy biodiesel's life-cycle GHG emissions.

It is important to note that GTAP modeling results for switchgrass and *Miscanthus* as ethanol feedstocks are largely driven by yield of these two crops which can in fact vary with location and management practices. Higher yielding biofuel feedstocks induce less LUC and therefore lower LUC GHG emissions. Results for *Miscanthus* and switchgrass ethanol can therefore be interpreted as representing results for high and lower yielding crops, respectively.

Table 8. Selected CCLUB Summary Results for Feedstock-to-Ethanol Pathways (g CO_2e/MJ), updated September 30, 2018

	Emission Factor Source	Corn 2011 CT	Corn 2011 NT	Corn 2013 CT	Corn Stover CT	*Miscan-thus*	Switch -grass	Soy CARB Avrg [d]	Soy GTAP 2011[d]
Domestic emissions	CENTURY /COLE[b]	2.6	1.1	-1.8	-0.2	-22.3	-10.4	0.9	-0.2
International emissions	Winrock	5.4	5.4	6.0	-0.4	2.3	7.5	11.0	8.1
Total[c]		8.0	6.5	4.2	-0.6	-20.0	-2.9	11.9	7.9

a. Per Heath *et al.* as explained in Section 4
b. CENTURY/COLE modeling with yield increase at 100 cm soil depth
c. May not be the exact sum of domestic and international emissions due to rounding
d. The soy biodiesel scenarios correspond to Case S2 and S4 in Table 2, respectively.

In future work we intend to address several outstanding issues. For example, current SOC modeling of conversion to cropland assumes that cropland is essentially planted in corn, but GTAP results may indicate other crops could be planted as well as part of crop switching as discussed in Section 2. We may seek to model transitions to specific crop types beyond corn and soy. Secondly, we currently model the land use history of cropland-pastureland as 50 years as cropland followed by 25 years of pasture and 25 years of cropland. Actual land use history may include more frequent changes between these two land uses. We may develop SOC emission factors for land transitions involving cropland-pastureland that reflect a more defined land use history. We began to investigate this question to some extent in Emery *et al*. (2017).

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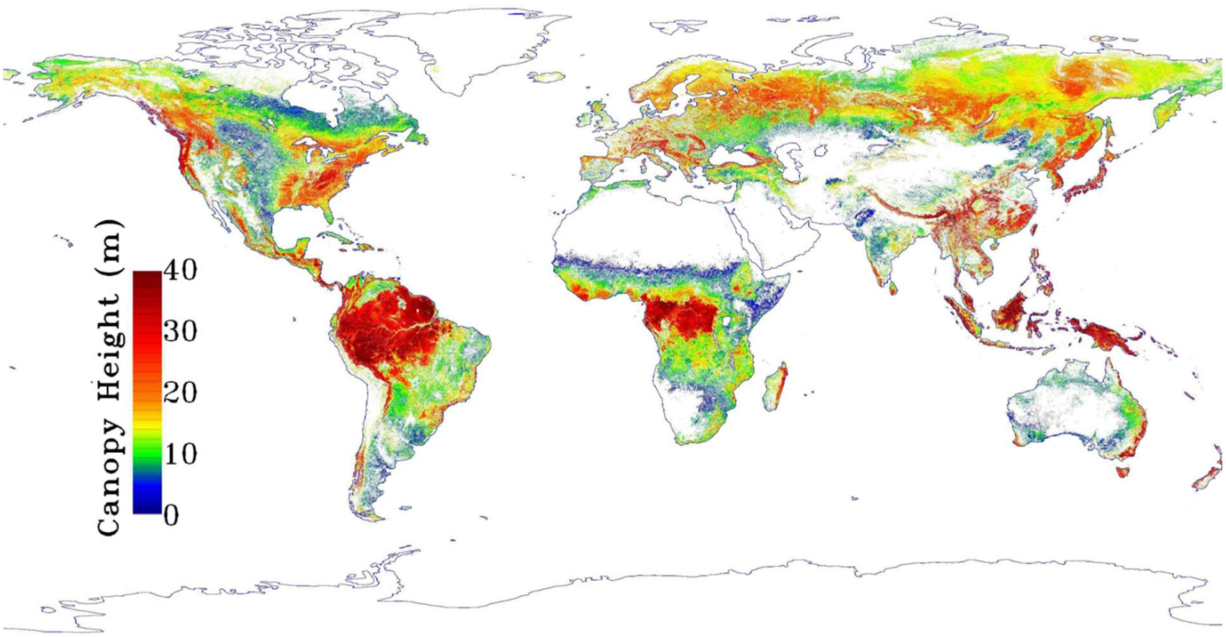
Appendix A: Global Map of Forest Height



Source: Alan Buis, Jet Propulsion Laboratory, Pasadena, Calif. Global map of forest height produced from NASA's ICESAT/GLAS, MODIS and TRMM sensors.
http://www.nasa.gov/topics/earth/features/forest20120217.html

Appendix B: Tabular Summary of Land Conversions

Scenario	Historic land use	1880-1950	1951-2010	2011-2040		
				Crop	Tillage	R (%)[1]
1	Grasslands	Croplands	Croplands	Corn	CT	0
2				Corn	CT	30
3				Corn	RT	0
4				Corn	RT	30
5				Corn	NT	0
6				Corn	NT	30
7				Switchgrass	NT	90
8				*Miscanthus*	NT	90
9				Poplar	NT	90
10				Willow	NT	90
11	Grasslands	Grasslands	Grasslands	Corn	CT	0
12				Corn	CT	30
13				Corn	RT	0
14				Corn	RT	30
15				Corn	NT	0
16				Corn	NT	30
17				Switchgrass	NT	90
18				*Miscanthus*	NT	90
19				Poplar	NT	90
20				Willow	NT	90
21	Forests	Forests	Forests	Corn	CT	0
22				Corn	CT	30
23				Corn	RT	0
24				Corn	RT	30
25				Corn	NT	0
26				Corn	NT	30
27				Switchgrass	NT	90
28				*Miscanthus*	NT	90
29				Poplar	NT	90
30				Willow	NT	90
31	Grasslands	Croplands	Grasslands (1951-1975)-Croplands (1976-2010)	Corn	CT	0
32				Corn	CT	30
33				Corn	RT	0
34				Corn	RT	30
35				Corn	NT	0
36				Corn	NT	30
37				Switchgrass	NT	90

Continued next page…

Continued

38	*Miscanthus*	NT	90
39	Poplar	NT	90
40	Willow	NT	90

[1]R is Residue or biomass removal rate (%) simulated in the model. This table contains 40 land conversions modeled in surrogate CENTURY. The results are contained in CCLUB.

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